

The association between COVID-19 data and meteorological factors in Indonesia

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1 **The association between Covid19 data and meteorological factors in Indonesia**

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25 **The association between Covid19 data and meteorological factors in Indonesia**

26

27

Abstract

28

29 On March 2, 2020, the first *Coronavirus Disease* (COVID-19) case was reported in Jakarta,
30 Indonesia. One and half month later (15/05/2020), the cumulative number of infection cases was
31 16496 with a total of 1076 mortalities. This study is aimed to investigate the possible role of
32 weather in the early cases of COVID-19 incidence in six selected cities in Indonesia. Daily data of
33 temperature and relative humidity from weather stations nearby each city were collected during
34 the period 3 March - 30 April 2020, together with data of COVID-19 cases. Correlation tests and
35 regression analysis were performed to examine the association of those two data series. In addition,
36 we analysed the distribution of COVID-19 with respect to weather data to estimate the effective
37 range of weather data supporting COVID-19 incidence. Our results reveal that weather data is
38 generally associated with COVID-19 incidence. The daily average temperature (T-ave) and
39 relative humidity (RH) presents significant positive and negative correlation with COVID-19 data,
40 respectively. However, the correlation coefficients are weak with the strongest correlations found
41 at 5 day lag time i.e. 0.37 (-0.41) for T-ave (RH). The regression analysis consistently confirmed
42 this relation. The distribution analysis reveals that the majority of COVID-19 cases in Indonesia
43 occurred in the daily temperature range of 25-31°C and relative humidity of 74-92%. Our findings
44 suggest that COVID-19 incidence in Indonesia has a weak association with weather conditions.
45 Therefore, non-meteorological factors seem to play a larger role and should be given greater
46 consideration in preventing the spread of COVID-19.

47

48 **Keywords: temperature, relative humidity, weather, COVID-19, Indonesia**

49

50 Introduction

51 The world was stirred by the spread of the Corona virus in Wuhan, China, starting in
52 January 2020, which caused local authorities to impose lockdowns in several affected cities [1–5].
53 In mid-latitude countries in the northern hemisphere (US, Italy, Spain, Iran, UK, Germany, etc.)
54 the number of patients exposed to the Corona virus Disease 2019 (COVID-19) was increasing. On
55 11 March 2020, the World Health Organization (WHO) declared COVID-19 as a pandemic due to
56 its global spread [6]. Uniquely, cases in China as the country of origin COVID-19 have declined.
57 The spread of COVID-19 to tropical countries including Indonesia was also becoming increasingly
58 massive. With a total population of nearly 270 million [7], Indonesia is a vulnerable country to
59 such a fast spreading infectious disease.

60 On March 2, 2020, the Indonesian government announced the first and second cases of
61 COVID-19 infection of two Depok citizens, outside of Jakarta City [8]. The contact tracing showed
62 that transmission to those citizens occurred at an event held on February 14, 2020 in Jakarta. There
63 were foreign citizens attending the event among whom later one person was confirmed infected
64 by the disease. Four days after the first case, another case of COVID-19 was found and afterwards
65 the disease continued to spread. The development of the cumulative rate rapidly followed an
66 exponential pattern. On 15 May, the total of COVID-19 cases reported over all 34 Indonesian
67 Provinces was 16,496 with a total of 1076 mortalities
68 (<https://www.worldometers.info/coronavirus/>).

69 The emergence of COVID-19 cases in Indonesia triggered discussions related to the risk
70 of COVID-19 transmission in tropical countries with a warm and humid climate that is very
71 different from the conditions where the disease was first found. Some previous studies revealed
72 that countries located in high altitudes with low temperatures and low humidity have a higher
73 vulnerability compared to tropical countries. They generally found that COVID-19 transmissions
74 were influenced by weather conditions such as temperature [9–15], relative humidity [13,14,16–
75 18] and precipitation [19,20]. Some of these studies indicated that ideal conditions for the corona
76 viruses are temperatures of around 8-10 °C with a relative humidity of about 60-90% [21,22].
77 Research by Bannister-Tyrrell et al., [9] also found a negative correlation between temperature
78 (above 1 °C) and the estimated number of COVID-19 cases per day. They showed that COVID-
79 19 had optimum dispersion at very low temperatures (1-9 °C). This indicates that in countries with
80 high temperatures and high humidity the risk of COVID-19 transmission is actually minimum.

81 On the other hand, the current situation shows that tropical countries are also vulnerable to
82 COVID-19 exposure. Many tropical countries currently have a high number of COVID-19
83 confirmed cases (per 15 May 2020) such as Brazil (218,223), India (85,784 cases), Ecuador
84 (31,467 cases), Singapore (26,891 cases) (<https://www.worldometers.info/coronavirus/>).
85 Additionally, recent publications by Auler et al., [17] and Luo et al., [23] reported COVID-19
86 cases also thrived in high temperatures , a contradictory conclusion to previous studies [21,24].
87 This discrepancy in research results suggests that the role of weather factors on COVID-19
88 transmission is still an open question and topic of debate [24,25].

89 In Indonesia, the association between weather conditions and COVID-19 cases has been
90 studied by Asyary and Veruswati, [27] and Tosepu et al., [26]. Tosepu et al., [26] found that
91 temperature significantly correlates to COVID-19 cases while Asyary et al [27] reported that

92 sunlight exposure increased the recovery rate of COVID-19. However, the studies were done over
93 a very short period (one month) and only in one city, i.e. Jakarta. Extending those previous studies
94 in Indonesia, this study aims to comprehensively investigate the role of weather factors in the
95 incidence of COVID-19 in several cities in Indonesia. While the role of social and behavioural
96 factors have been documented considerably (see for example Lakshmi Priyadarsini and Suresh,
97 [28]), literature reporting a robust role of meteorological factors on the COVID-19 transmission,
98 particularly in tropical countries is still scarce.

99 Data and Methodology

100 Data

101 Six cities were selected for this study (See Figure 1-a) considering their cumulative
102 confirmed cases (see Figure 2), their location in the country (north-south of equator line and
103 western-eastern part of the country) to capture variations in climate (see Figure 1-b, 1-c) and the
104 distribution of cases throughout the country. Those six cities are Medan, Jakarta, Bogor, Surabaya,
105 Denpasar, and Makassar. Specifically, Medan is a representative of cities located north of the
106 equator, Bogor is a representative of cities with a relatively high elevation (colder climate) and
107 Denpasar and Makassar are representatives of the eastern part of Indonesia (Table 1).

108

109

110 Daily surface weather data for March-April 2020 were collected from the nearest weather
111 station for each city (see Table 2). We selected four weather variables i.e. average temperature (T-
112 ave), minimum temperature (Tmin), maximum temperature (Tmax) and average relative humidity
113 (RH). Those are variables most frequently investigated in previous COVID-19 studies
114 [19,20,29,30]. T-ave and RH were computed from hourly observations (24 data per day). In
115 addition, we also computed the diurnal temperature range (DTR, Tmax minus Tmin) and absolute
116 humidity (AH). AH was computed following a method used by Luo et al., [23]. Different from
117 RH, AH is a variable describing the actual amount of water vapour in the atmosphere. Previous
118 studies have shown that AH is more correlated to the disease compared to RH [31,32]. To provide
119 climate background of the country, the daily mean temperature and relative humidity from
120 NCEP/NCAR Re-analysis data [33] for March-April during 1981-2010 were used.

121 Daily data of new cases of COVID-19 were gathered from each local government website
122 (see Table 2). The period of data varies depending on the timing of the first case of COVID-19
123 found in the respective city, as shown in Table 1. For Makassar city, the COVID-19 data used was
124 the total for South Sulawesi Province since data for Makassar was not available online. However,
125 we assumed that this province level data was still valid for Makassar city considering that the
126 majority of COVID-19 cases in South Sulawesi Province occurred in that city. Only days with
127 non-zero COVID-19 data were included in the analysis.

128 Method

129 A descriptive statistical analysis was performed both at city and country level (all data
130 together) to explore the characteristics of confirmed case counts and weather data. Two approaches
131 were then employed to find out the potential association between the incidence of COVID-19 and

132 weather data i.e. correlation tests and non-linear regression analysis. The correlation test was done
133 for several options of lag time [16,30] to consider the incubation period of COVID-19, which is
134 on average around 5-6 days [34]. This lag time technique is also intended to accommodate the lag
135 effect of medical tests to confirm COVID-19 cases. It is known that COVID-19 reported on a
136 certain day might be due to transmission occurring several days before. In Indonesia, PCR testing
137 (polymerase chain reaction) usually takes several days to complete [35,36] so that confirmed cases
138 are published several days after the time of infection. Our next analysis was based on the best lag
139 time identified from the correlation test (i.e. lag time with the strongest coefficient of correlation).
140 Additionally, to examine associative relationships between weather data and COVID-19 data, the
141 nonlinear regression analysis was employed following a method by Luo et al. [23]. As the last
142 step, we analysed the distribution of COVID-19 data with respect to weather data to point out a
143 possible consistent range of weather data favoured by COVID-19 incidence [37]. This was done
144 by visualizing COVID-19 data on a scatter plot and drawing the contour of 90% data density. This
145 means that the majority of COVID-19 data falls within the contour. By projecting the contour to
146 the weather data (x-axis), we were able to locate the effective range of weather data favouring the
147 COVID-19 incidence.

148 Results and Discussions

149 Results

150 Meteorological Condition

151 The climatology of temperature and relative humidity during March-April is shown in
152 Figure 1-b and 1-c. Based on NCEP/NCAR Re-analysis data, the March-April temperature in

153 Indonesia ranges from 22-28 °C while relative humidity ranges from 70-95%. Figure 3 shows the
154 boxplot that represents the descriptive statistics for daily meteorological variable and case numbers
155 of COVID-19 for each city. During March-April 2020, a large variation of the weather conditions
156 was observed in six selected cities in Indonesia. Generally, March and April are months with high
157 monthly rainfall but some parts of eastern Indonesia start to have a dry season onset. Jakarta,
158 Surabaya and Denpasar have the highest T-ave while Bogor has the lowest one among the six
159 cities. For DTR, the lowest (highest) value was found in Jakarta (Bogor). As expected, unlike T-
160 ave, the highest RH was found in Bogor while Jakarta and Surabaya share a nearly similar range
161 of RH data. For AH data, on the other hand, Medan had the highest mean and Bogor had the lowest
162 value. As shown in Figure 3, the range of AH data does not seem connected to other weather data
163 confirming its specific characteristics. In addition, we noted that Denpasar presented a narrow
164 range for T-ave, DTR and RH suggesting small variation of weather there.

165 The COVID-19 data, on the other hand, shows a large discrepancy among cities, with
166 Jakarta having the largest number of confirmed cases. Jakarta as the main international gate to the
167 country is the place where the first case of COVID-19 was found indicating the high risk of Jakarta
168 to this disease. During the study period (Table 1), there were a total of 4138 COVID-19 cases in
169 Jakarta. On average, there were approximately 75 cases of COVID-19 per day in Jakarta, and less
170 than 50 cases per day in other cities. With a population of 11 million, Jakarta is the centre of
171 national transmission of COVID-19 and early cases in other cities were mostly related to events in
172 Jakarta.

173 Correlation Test

174 The correlation of the weather variables and COVID-19 data is presented in Figure 4.
175 Except for AH, weather variables show statistically significant correlation for all lag times. Our
176 test found that T-ave is positively correlated with COVID-19 cases even though the coefficient
177 correlation (r) is weak with the highest r value of 0.37 found for 1 and 5 days lag time. In contrast,
178 DTR and RH present a significantly negative correlation with relatively similar r values. The
179 strongest correlation for DTR was found for 8 days lag time ($r = -0.39$) and that for RH was found
180 for 5 days lag time ($r = -0.41$). On the other hand, AH shows the weakest correlation to the COVID-
181 19 data, with r values ranging from -0.03 to 0.05. Based on the T-ave and RH data, it was observed
182 that the strongest correlation was found for 5 days lag time. This lag time probably indicates the
183 average incubation period of COVID-19 in Indonesia and this is in agreement with the WHO
184 statement about this matter [34]. Another possibility is that this 5 days lag time may represent the
185 average interval between timing of infection and diagnosis by PCR test. However, when looking
186 at each city (Table 3, Supplementary Material), the r value and the lag time having the strongest
187 correlation vary among cities.

188 Regression Analysis

189 The results of a nonlinear regression analysis between weather variables and COVID-19
190 data on 5 days lag time are visualized in Figure 5. In general, the coefficient of determination (R^2)
191 for all variables is less than 20%, indicating that only a small part of variance of COVID-19 data
192 can be explained by weather variability. However, considering the statistically significant
193 correlation between those two data, it is worth discussing the characteristics of COVID-19 data
194 with respect to the range of weather data in this study.

195 As shown in Figure 5, the plot suggests that the confirmed number of cases increased with
196 an increase of temperature, in the range of 25-31°C. In contrast, in the range of 3-11°C (65-95%),
197 the confirmed cases declined as the DTR (RH) increased. On the other hand, the AH presents a
198 different pattern of relationships with more confirmed cases found at the AH of around 18-20
199 g/m³, the middle part of all distributions.

200 Distribution Analysis

201 To get an idea of the effective range of weather data favouring COVID-19 transmission in
202 Indonesia, we analysed the distribution of COVID-19 data with respect to T-ave, DTR, RH, and
203 AH, as shown in Figure 6. During March-April 2020, 90% of confirmed cases in the six selected
204 cities (shown by contour on the scatter plot) occurred in the range of T-ave approximately between
205 25-31°C. Additionally, the bounds of DTR of 90% of total confirmed cases was around 4-11 °C,
206 and that of RH (AH) was about 74-92% (17-21 g/m³). Outside of those bounds, the number of
207 confirmed cases were generally low. For instance, for T-ave > 31 or RH < 74%, the number of
208 confirmed cases was minimum. These results may indicate the particular range of weather
209 conditions that favour COVID-19 incidence.

210 Discussion

211 This is the first time that the link between meteorological factors and COVID-19 incidence
212 in multi-cities in Indonesia has been investigated comprehensively. Our study extends the research
213 by Tosepu et al [26] which examines the correlation between weather and COVID-19 pandemic
214 in Jakarta, Indonesia. Our work also contributes to the insight into the characteristics of COVID-
215 19 cases particularly in tropical climates which are still limited in the literature [17]. It is known

216 that most of the research on the link of weather data and COVID-19 cases available in the literature
217 comes from sub-tropical countries [29,38,39].

218 We found that during the study period, the daily average temperature positively correlated
219 to the COVID-19 cases, in agreement with previous studies reported by Auler et al., [17], Liu et
220 al., [30] and Tosepu et al., [26]. In contrast, DTR and RH present a significant negative correlation
221 with COVID-19 data while AH shows an inconsistent correlation among all lag times studied. Our
222 findings on the role of T-ave and DTR are consistent with the study by Liu et al [30] who found
223 that the number of confirmed cases in China during the period of January 20th to March 2nd, 2020
224 tended to increase (decline) following an increase in temperature (DTR). It was also found in our
225 study that a lag time of 5 days presented the strongest correlation for T-ave and RH which probably
226 indicates the average time between exposure and diagnosis.

227 The link between weather data and the COVID-19 data was also confirmed by the results
228 of regression analysis with a 5-day lag time. As shown in Figure 5, we observed that the number
229 of confirmed cases increased following an increase in temperature, or the decrease of DTR and
230 RH. These findings indicate that the COVID-19 incidence may be partially affected by
231 meteorological factors. However, it is important to mention that both the coefficient correlation
232 and coefficient of determination was considerably low i.e. about -0.4 to 0.4 and less than 20%,
233 respectively. This low value suggests that the effect of meteorological factors is limited and the
234 COVID-19 incidence might be largely influenced by non-meteorological factors. It seems that the
235 significant positive correlation between T-ave and COVID-19 data was found because the
236 temperature gradually increased from March to April following the seasonal change while at the
237 same time, the confirmed cases of COVID-19 increased due to the rapid spread of this disease.

238 Our findings are somewhat in contrast with previous studies conducted in regions with
239 colder climates which reported that the increase in temperature could reduce COVID-19
240 transmission [11,18]. They, in general, found that lower temperatures favoured COVID-19 cases.
241 However, later studies in China by Liu et al., [30] and in Brazil by Auler et al., [17] reveal that the
242 increase of temperature is followed by an increase of confirmed cases and high temperature
243 supports COVID-19 transmission as well. This contradictory finding indicates that the potency of
244 high temperature and high humidity in reducing the transmission of COVID-19 might not be valid
245 for tropical regions where the average temperature and relative humidity is climatologically high.
246 For instance, the six selected cities in Indonesia during the months March and April 2020 registered
247 a daily temperature of higher than 25 °C and a daily relative humidity of more than 65%. This
248 range of weather data is beyond the effective bound for COVID-19 cases suggested by previous
249 studies [21,22]. Furthermore, our distribution analysis revealed that the majority of COVID-19
250 cases (90% of cases) occurred within the temperature range of 25-31°C and RH range of 74-92%.
251 Our results are in agreement with the study by Auler et al., [17] who found that the COVID-19
252 transmission rate in Brazil was initially observed to be favoured by higher mean temperatures (27.5
253 °C) as well as intermediate relative humidity (near 80%).

254 We emphasize that this study presenting a preliminary analysis and the investigation was
255 limited to meteorological factors. A longer study period and more sampling of affected cities might
256 better represent the association between meteorological conditions and COVID-19 incidence. It
257 has been reported that, besides being influenced by meteorological factors, the number of
258 confirmed COVID-19 cases in a country depends on multiple factors including the extent of testing
259 conducted [40], population [19,29], social dynamics/migration scale [10,41,42], governmental
260 policies such as the limitation of public transport [38,43,44] etc. In Indonesia, the number of daily

261 confirmed cases at national level is closely correlated with the extent of testing conducted with a
262 coefficient correlation of 0.71 suggesting that the detected confirmed cases depend largely on the
263 extent of testing conducted by the government (Figure 7).

264 Conclusions

265 Our study demonstrates that weather conditions are weakly associated with the COVID-19
266 incidence particularly in the six selected cities in Indonesia. This is the first comprehensive
267 research that has attempted to explore the effects of meteorological factors on the COVID-19 cases
268 in multi-locations in Indonesia, an example of a country with a tropical climate. Daily mean
269 temperature (diurnal range of temperature and relative humidity) present statistically positive
270 (negative) significant correlation to confirmed COVID-19 cases. During the selected study period,
271 March-April 2020, the majority of COVID-19 incidence in Indonesia was observed to occur in the
272 daily temperature range of 25-31°C and relative humidity of 74-92%. However, it should be noted
273 that the effect of meteorological factors is limited, considering the low value of coefficient
274 correlation and coefficient of determination presented in this study. Thus, non-meteorological
275 factors have to be considered to have more control over the COVID-19 pandemic.

276 Declaration

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278 Not applicable

279 **Conflicts of interest/Competing interests**

280 The authors declare that they have no known competing interests or personal relationships that
281 could have appeared to influence the work reported in this paper.

282 **Availability of data and material (data transparency)**

283 Not applicable

284 **Code availability (software application or custom code)**

285 Not applicable

286 **Authors' contributions**

287 Supari and D.E. Nuryanto contributed equally as the main contributor of this paper. All authors
288 were involved in reviewing and editing the original manuscript.

289

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413

414 **List of Tables**

415 **Table 1.** List of selected cities and their characteristics

CITY	ELEVATION	NORTH-SOUTH	WEST-EAST	PERIOD OF DATA
MEDAN	< 50 m	North	West	28 March 2020 – 30 April 2020
JAKARTA	< 10 m	South	West	2 March 2020 – 30 April 2020
BOGOR	> 250 m	South	West	21 March 2020 – 30 April 2020
SURABAYA	< 10 m	South	West	23 March 2020 – 30 April 2020
DENPASAR	< 100 m	South	East	1 April 2020 – 30 April 2020
MAKASSAR	< 25 m	South	East	15 March 2020 – 30 April 2020

416

417 **Table 2.** Source of weather and COVID-19 data for six selected cities

CITY	SOURCE OF WEATHER DATA	SOURCE OF COVID-19 DATA
MEDAN	Kualanamu Airport Weather Station	https://covid19.pemkomedan.go.id/
JAKARTA	Kemayoran Weather Station	https://corona.jakarta.go.id/id
BOGOR	Dramaga Climate Station	https://pikobar.jabarprov.go.id/
SURABAYA	Djuanda Airport Weather Station	https://lawanCOVID-19.surabaya.go.id/
DENPASAR	Ngurah Rai Airport Weather Station	https://safecity.denpasarkota.go.id/id/covid19
MAKASSAR	Hasanudin Airport Weather Station	https://covid19.sulseprov.go.id/

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421 List of Figures Caption

422 Figure 1. The map showing the location of six selected Indonesian cities and its elevation (a),
423 the climatology of daily temperature (b) and relative humidity (c) for March-April
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425 Figure 2. Time series of cumulative COVID-19 cases for selected cities during 1 March - 30
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427 Figure 3. The boxplot of meteorological data and new cases of COVID-19 in six selected
428 cities.

429 Figure 4. The correlation between meteorological factors and new cases of COVID-19 for
430 total (combination of six selected cities) for several options of lag times. Markers
431 denote statistically significant correlation.

432 Figure 5. Non-linear regression between meteorological data and COVID-19 cases. Blue to
433 red colour represents the timing of data from March – April 2020.

434 Figure 6. Scatter plot of COVID-19 data with respect to weather data. The red contour
435 represents the 90% of COVID-19 data density indicating the majority of data. Red
436 vertical lines are bounds of each weather variable with 90% of COVID-19 data
437 falling within those ranges.

438 Figure 7. Time series of daily testing numbers taken by the government and daily new cases
439 detected from the test.

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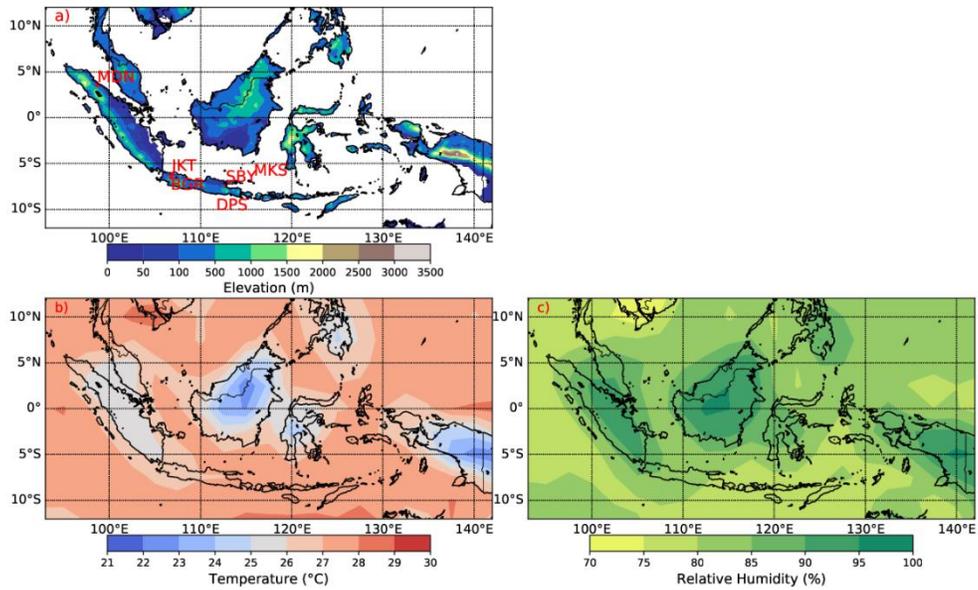


Figure 1

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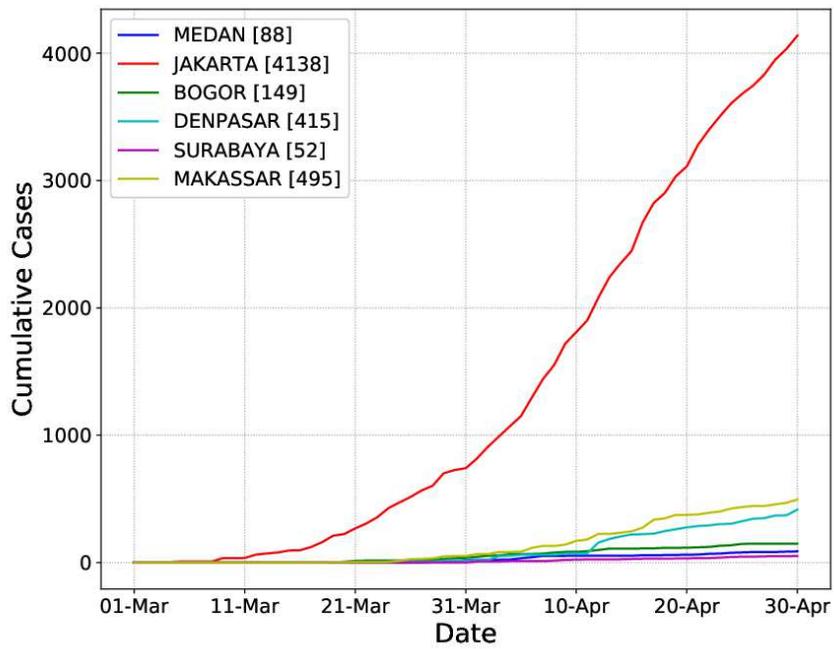
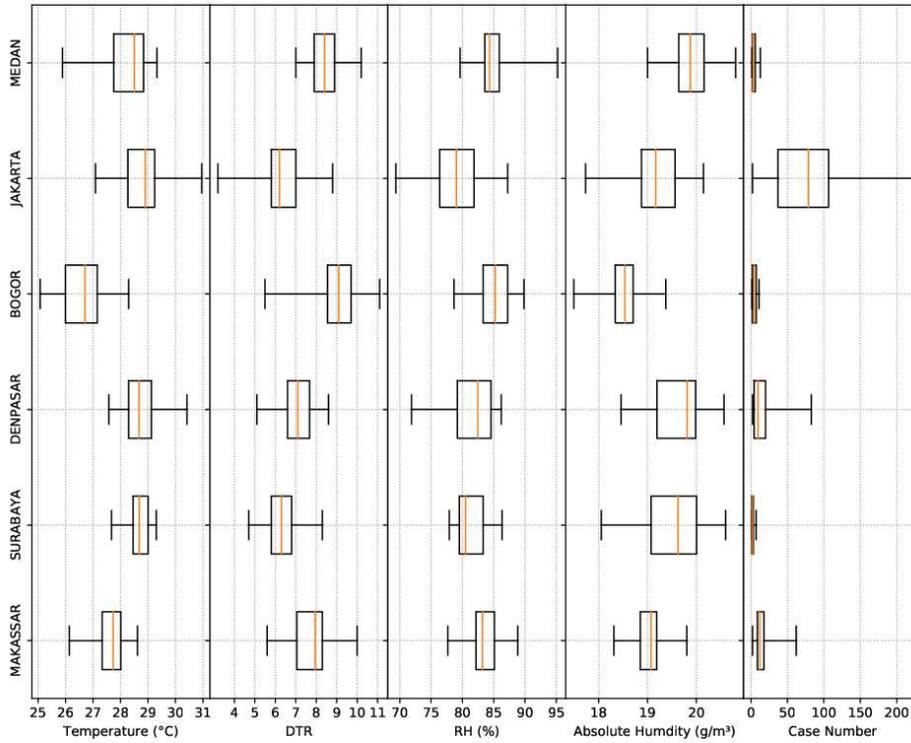


Figure 2

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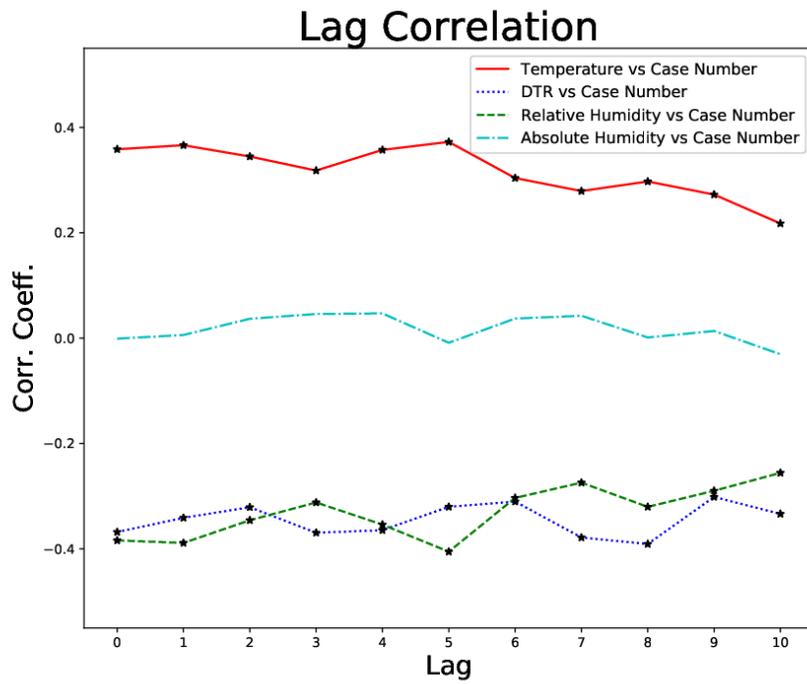
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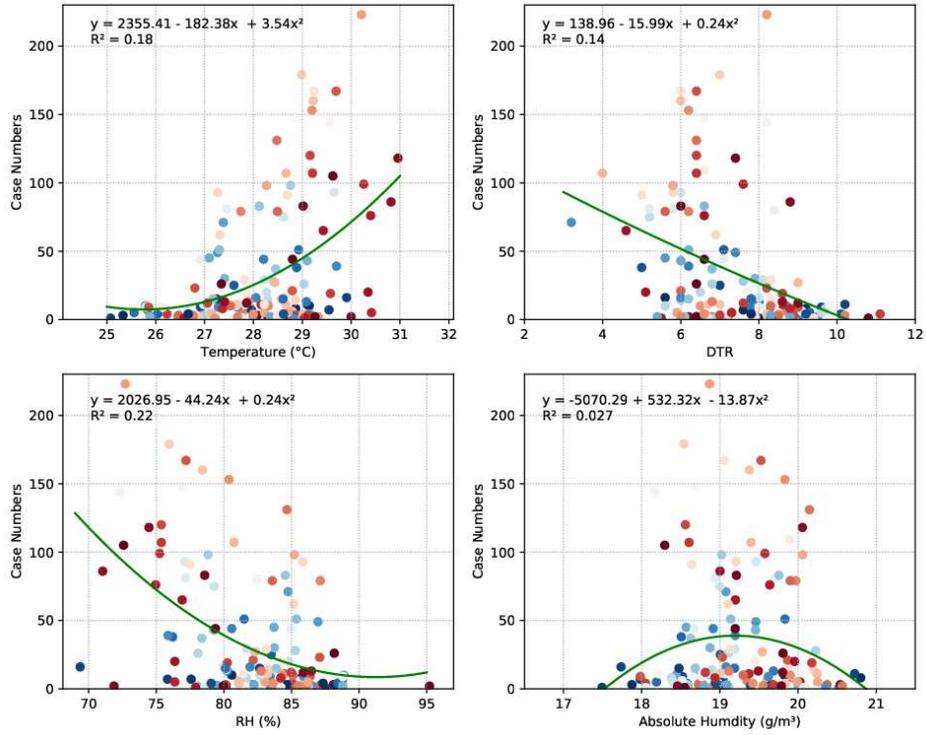
Figure 3



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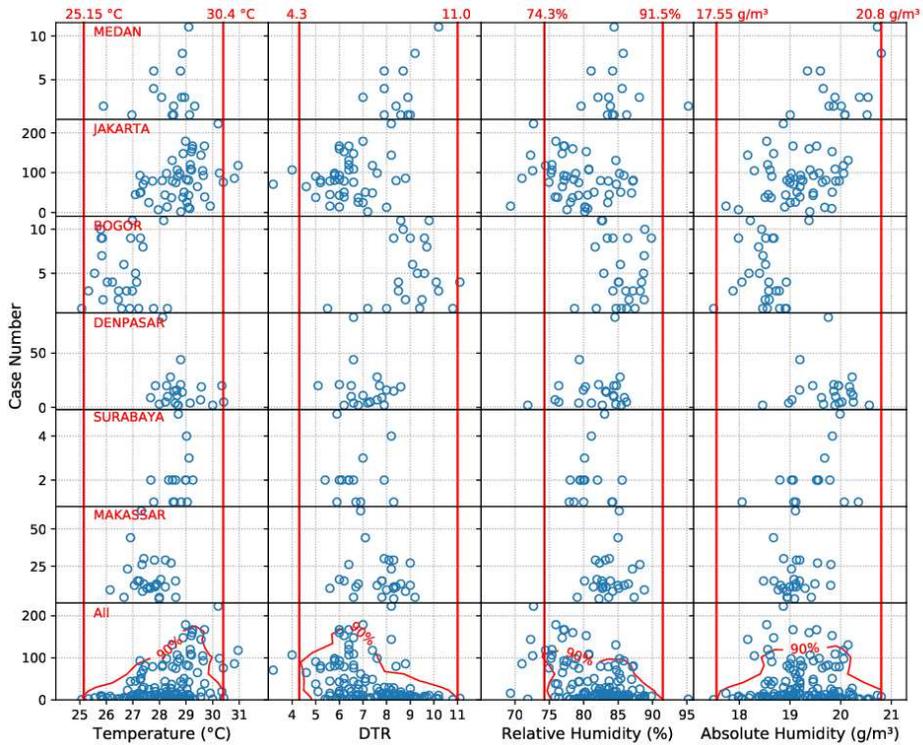
Figure 4



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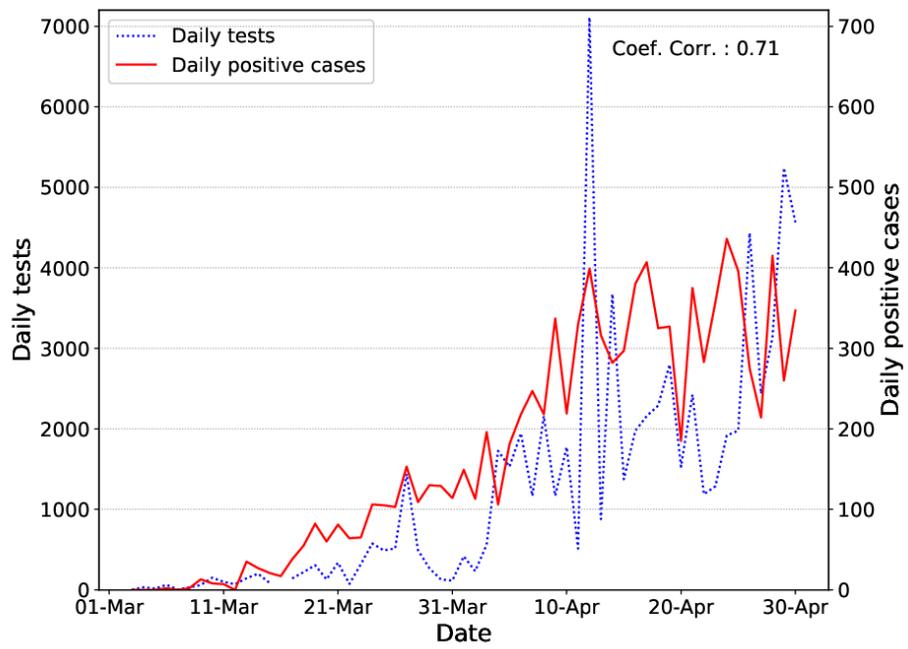
Figure 5



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Figure 6



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Figure 7

457 **Supplementary Material**

458 **Table 3.** Summary of lag correlation between meteorological parameters versus new cases of COVID-19 for each
 459 city. The asterisk symbol denotes statistically significant correlation.

Parameters	Lag	MEDAN	JAKARTA	BOGOR	DENPASAR	SURABAYA	MAKASSAR
Temperature	0	0.15	0.24	0.32	-0.14	0.32	-0.052
	1	-0.27	0.26	0.21	-0.099	0.29	0.095
	2	0.16	0.19	0.056	-0.18	0.29	0.064
	3	-0.037	-0.0012	0.27	0.13	-0.019	0.26
	4	0.5*	0.2	-0.079	-0.062	-0.19	-0.2
	5	0.25	0.33*	0.029	-0.2	0.25	-0.12
	6	0.34	0.032	-0.4*	0.19	-0.048	0.2
	7	0.28	-0.016	-0.17	-0.13	0.064	0.14
	8	-0.47	0.19	0.059	0.45*	-0.3	-0.41*
	9	0.088	0.16	0.016	0.049	-0.72*	-0.062
	10	-0.89*	0.056	-0.14	0.051	0.017	-0.086
DTR	0	0.56*	-0.088	0.17	0.078	0.025	-0.024
	1	0.08	0.037	0.053	0.14	-0.057	-0.11
	2	-0.1	0.11	-0.49*	-0.039	0.056	0.052
	3	0.088	-0.1	0.21	-0.051	-0.093	0.075
	4	0.46	-0.04	-0.11	0.26	-0.18	-0.29
	5	0.48	0.13	0.16	-0.16	-0.0063	-0.16
	6	0.2	0.12	0.35	-0.29	0.46	0.18
	7	-0.02	-0.13	0.055	-0.11	0.33	0.014
	8	-0.35	-0.093	-0.3	0.022	0.19	-0.19
	9	-0.55	0.095	-0.043	0.38	0.18	0.058
	10	-0.57	-0.038	-0.28	-0.24	-0.21	0.14
Relative Humidity	0	-0.003	-0.11	0.32	-0.068	-0.45*	0.081
	1	0.28	-0.12	0.21	0.023	-0.19	-0.067
	2	0.045	-0.025	0.056	0.003	-0.17	0.029
	3	0.062	0.15	0.27	-0.17	-0.056	-0.21
	4	-0.089	-0.044	-0.079	0.13	0.19	0.16
	5	-0.088	-0.24	0.029	0.16	0.15	0.14

	6	-0.095	0.084	-0.4*	-0.22	0.39	-0.13
	7	-0.47	0.15	-0.17	0.12	0.38	-0.13
	8	0.2	-0.054	0.059	-0.66*	0.1	0.36
	9	-0.25	-0.036	0.016	-0.064	-0.32	-0.041
	10	0.37	-0.0019	-0.14	-0.065	-0.26	0.0086
Absolute Humidity	0	0.29	0.17	0.32	-0.3	-0.21	0.059
	1	-0.034	0.19	0.21	-0.097	0.023	0.04
	2	0.38	0.25	0.056	-0.23	0.05	0.16
	3	0.049	0.27	0.27	-0.14	-0.07	0.12
	4	0.75*	0.23	-0.079	0.15	0.019	-0.091
	5	0.34	0.075	0.029	-0.00097	0.34	0.0094
	6	0.33	0.2	-0.4*	-0.13	0.34	0.17
	7	-0.046	0.24	-0.17	-0.018	0.4	0.074
	8	-0.44	0.19	0.059	-0.48*	-0.098	-0.3
	9	-0.1	0.18	0.016	-0.046	-0.61*	-0.24
	10	-0.81*	0.068	-0.14	-0.046	-0.19	-0.2

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Figures

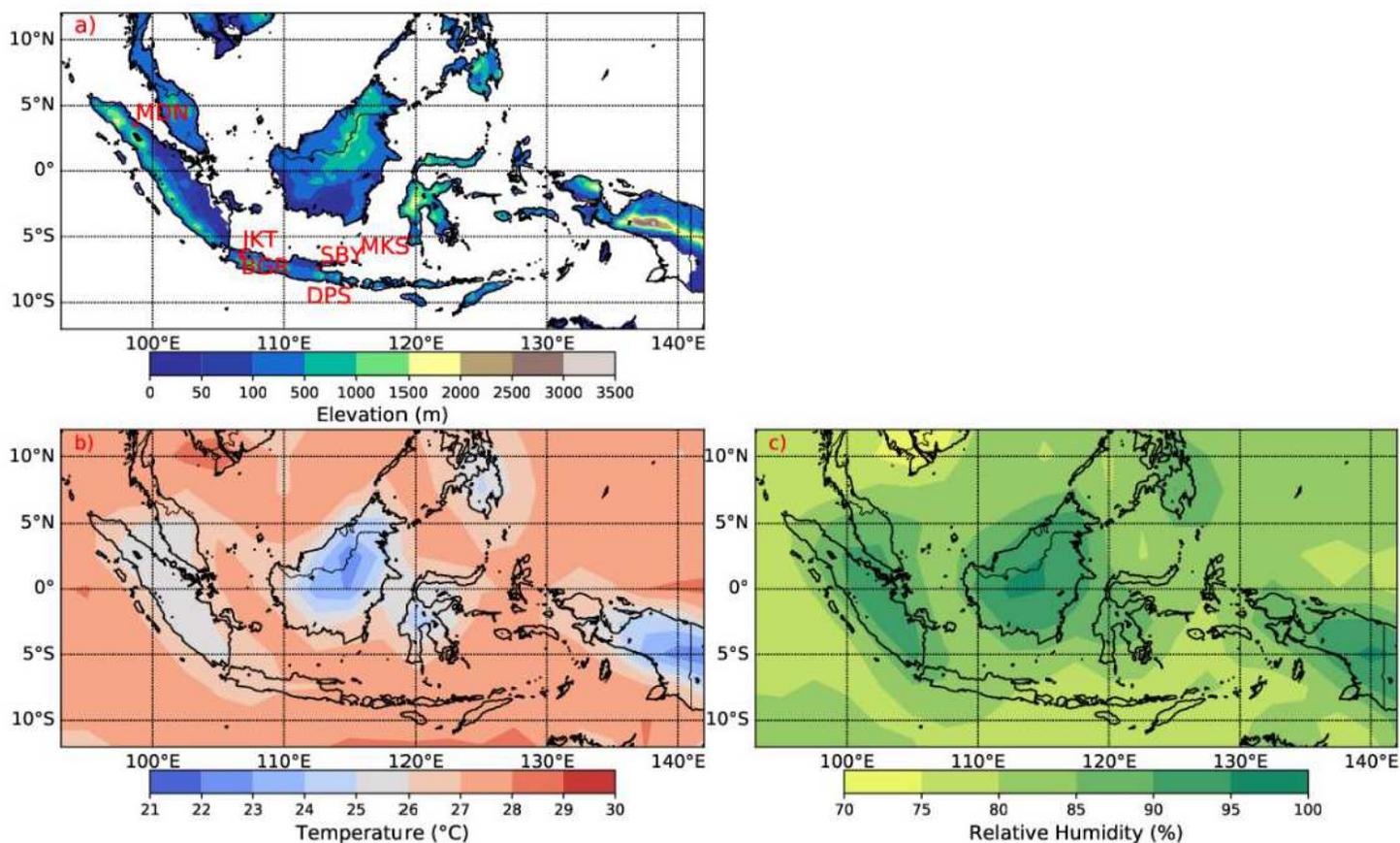


Figure 1

The map showing the location of six selected Indonesian cities and its elevation (a), the climatology of daily temperature (b) and relative humidity (c) for March-April based on NCEP/NCAR Re-analysis data. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

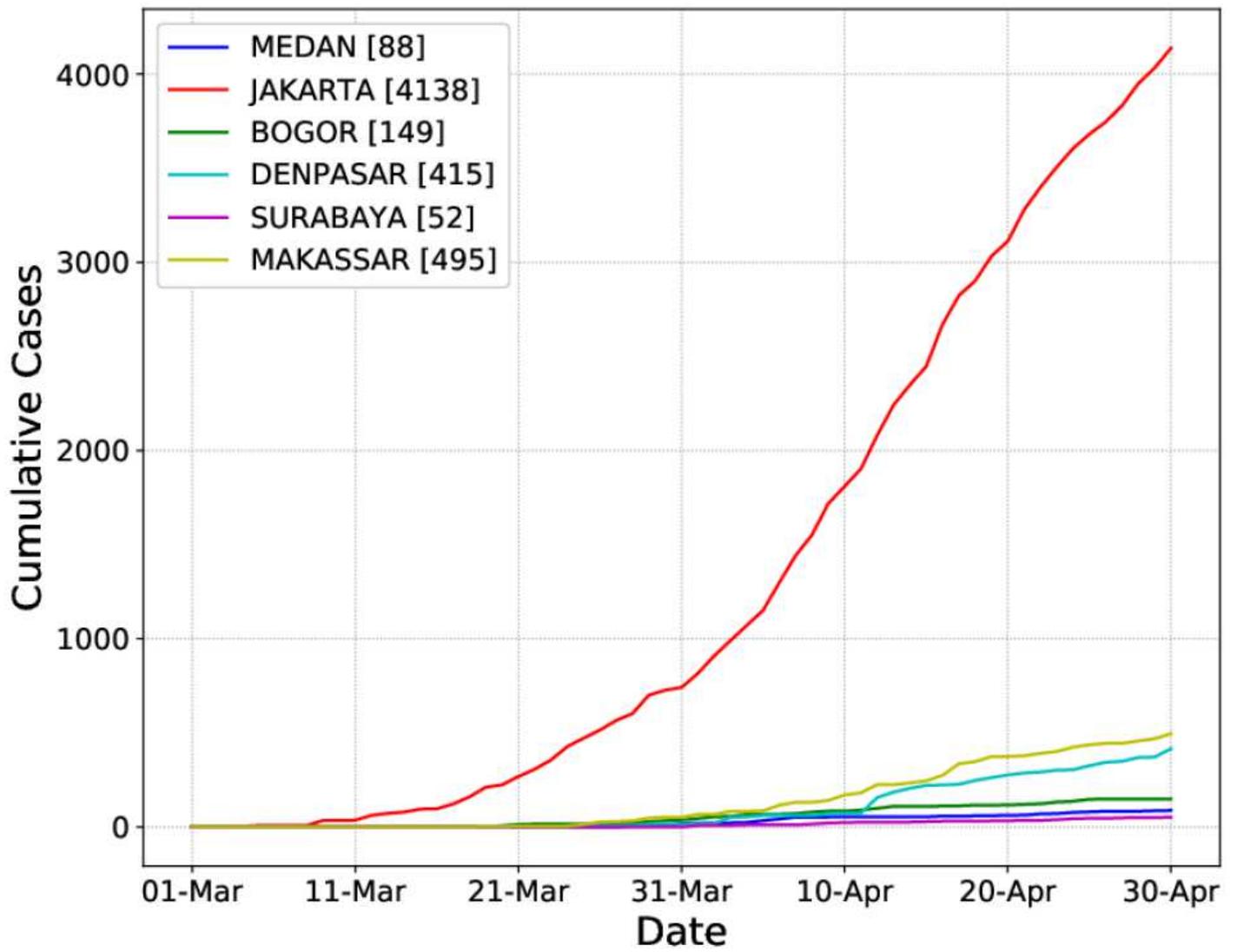


Figure 2

Time series of cumulative COVID-19 cases for selected cities during 1 March - 30 April 2020.

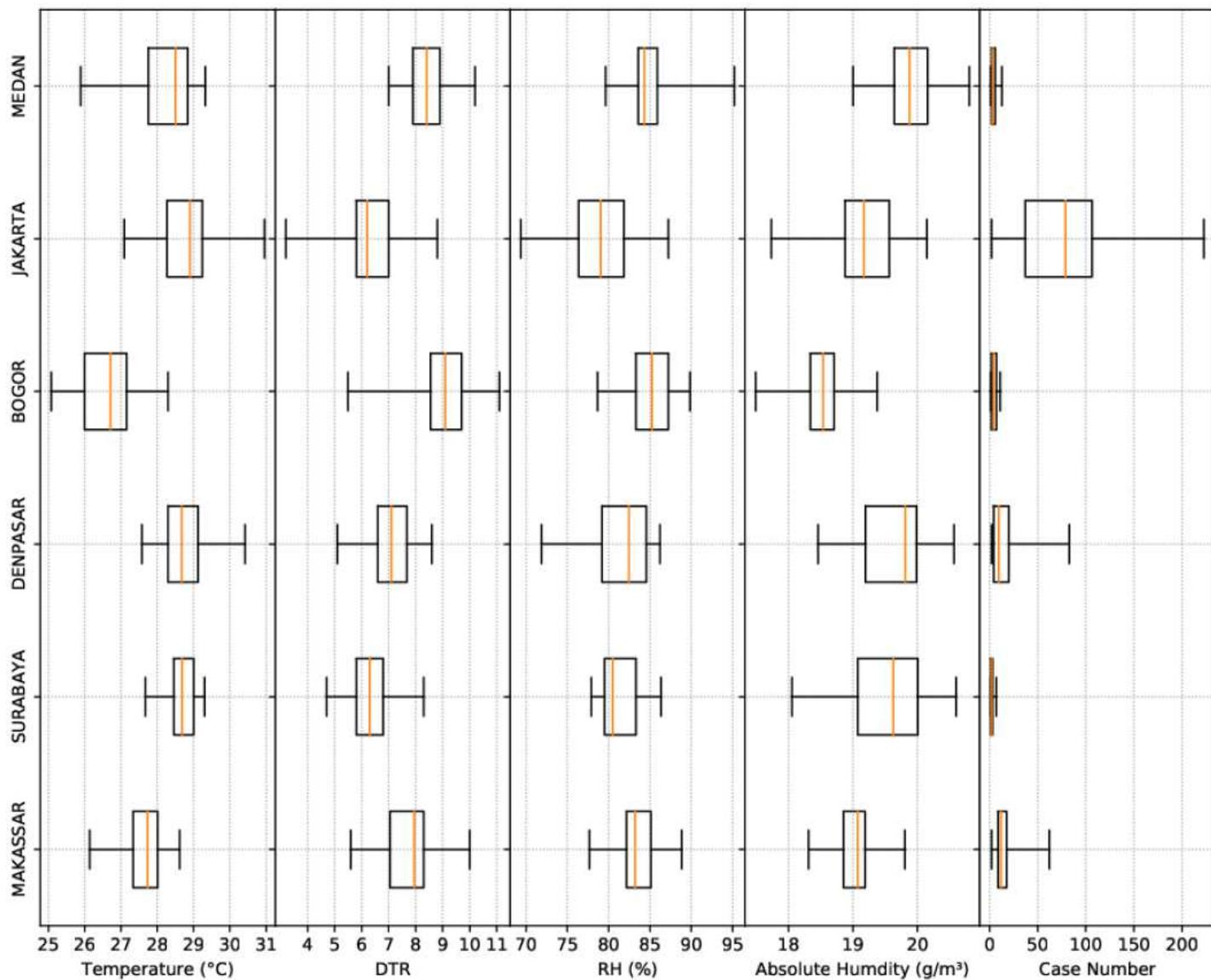


Figure 3

The boxplot of meteorological data and new cases of COVID-19 in six selected cities.

Lag Correlation

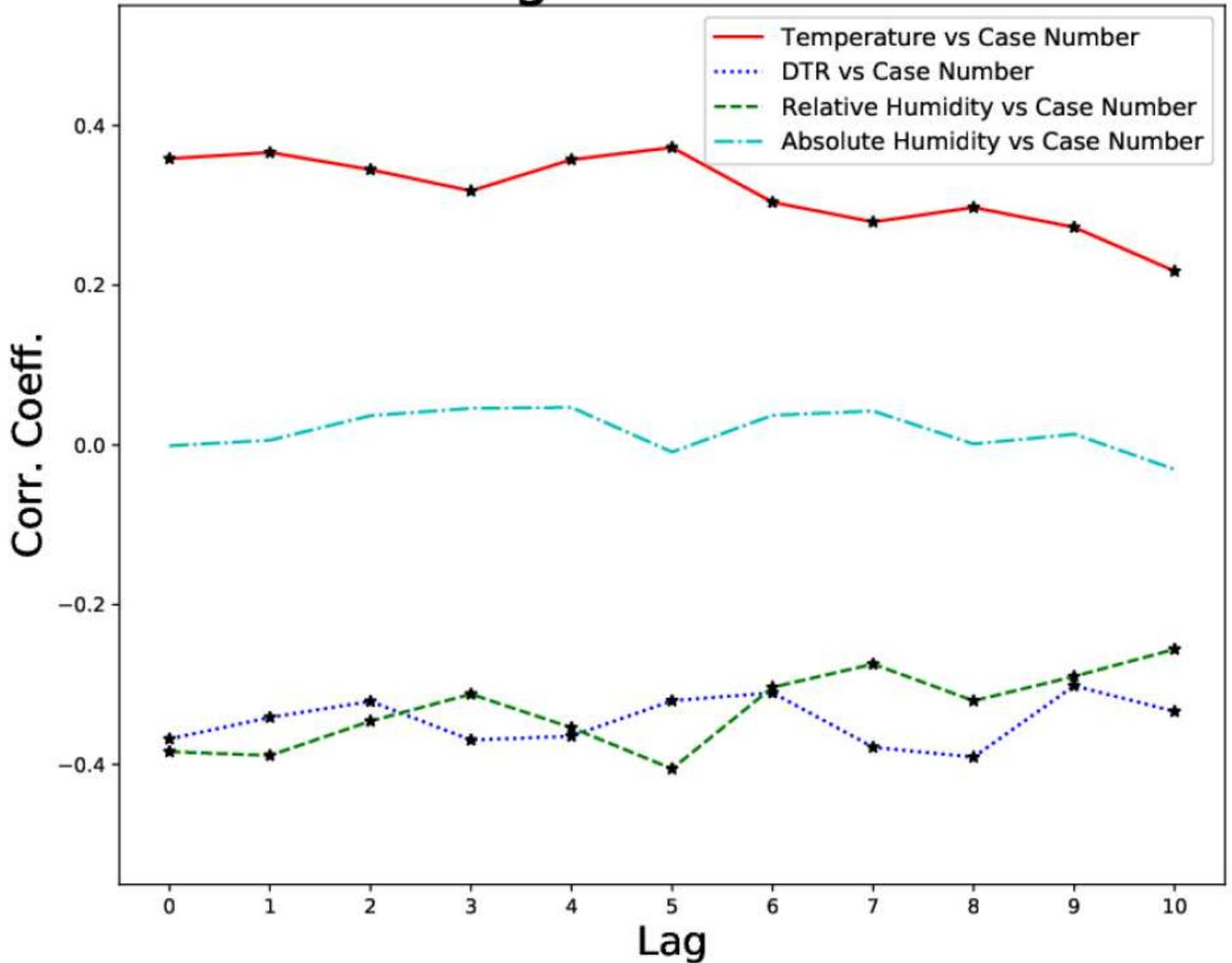


Figure 4

The correlation between meteorological factors and new cases of COVID-19 for total (combination of six selected cities) for several options of lag times. Markers denote statistically significant correlation.

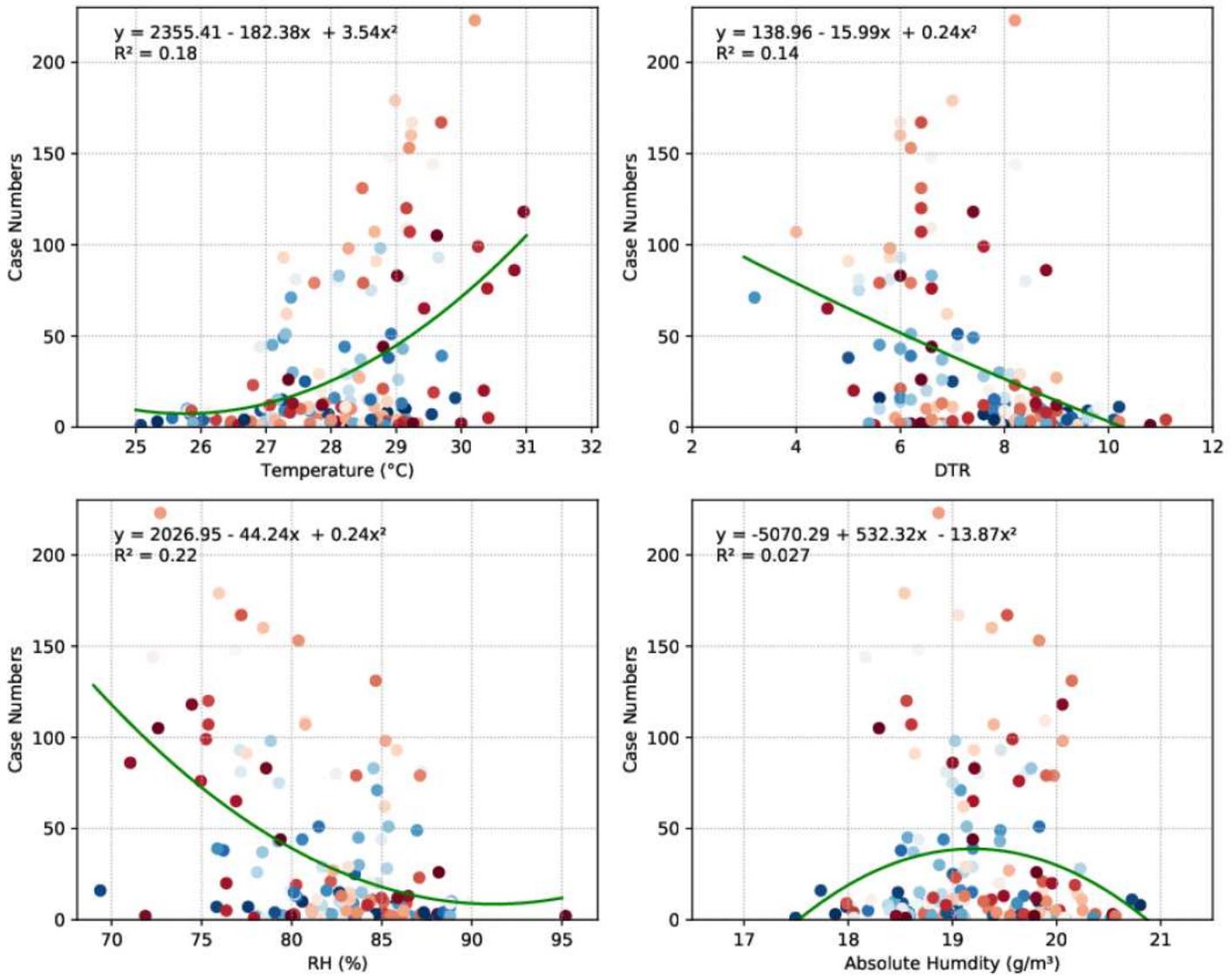


Figure 5

Non-linear regression between meteorological data and COVID-19 cases. Blue to red colour represents the timing of data from March – April 2020.

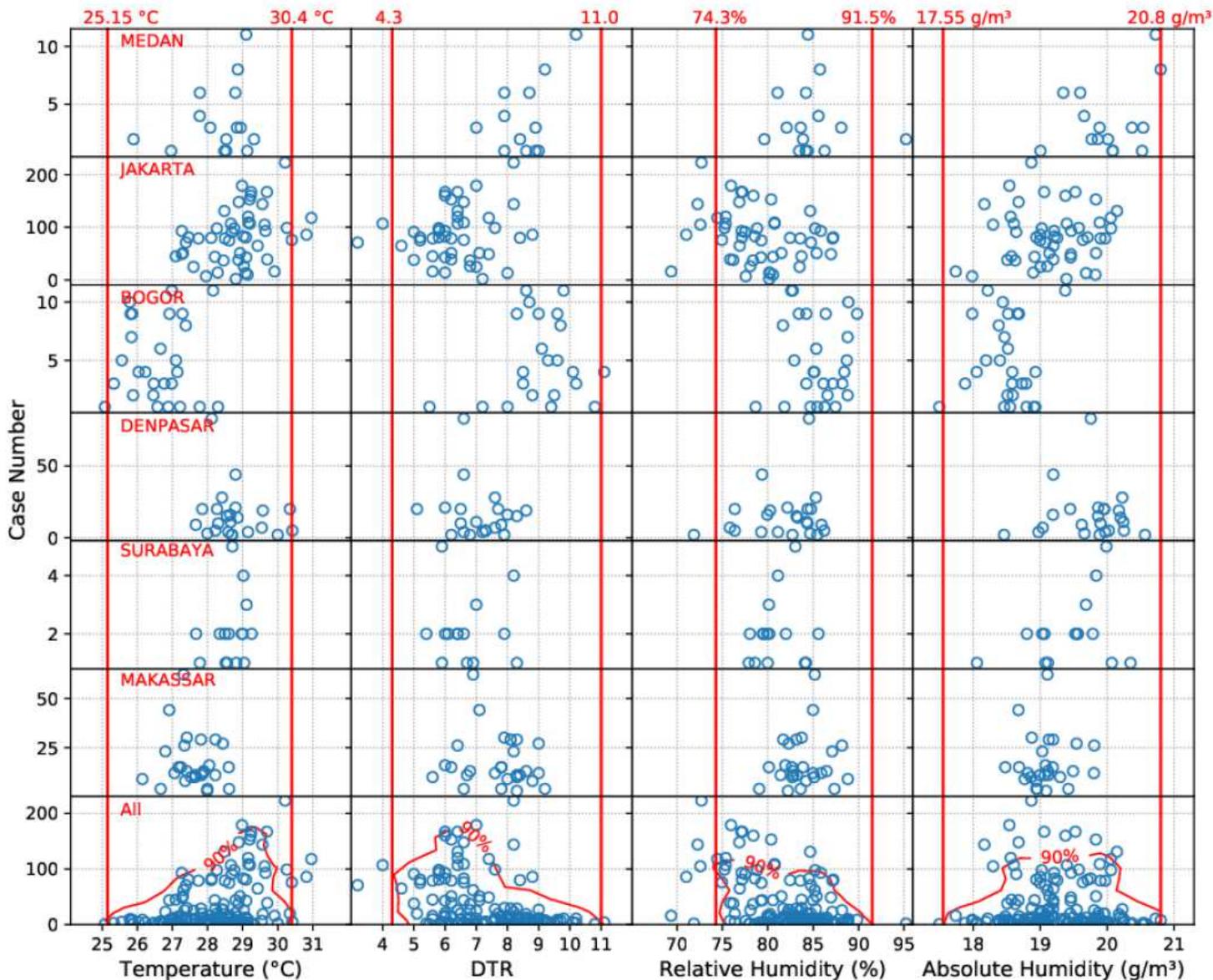


Figure 6

Scatter plot of COVID-19 data with respect to weather data. The red contour represents the 90% of COVID-19 data density indicating the majority of data. Red vertical lines are bounds of each weather variable with 90% of COVID-19 data falling within those ranges.

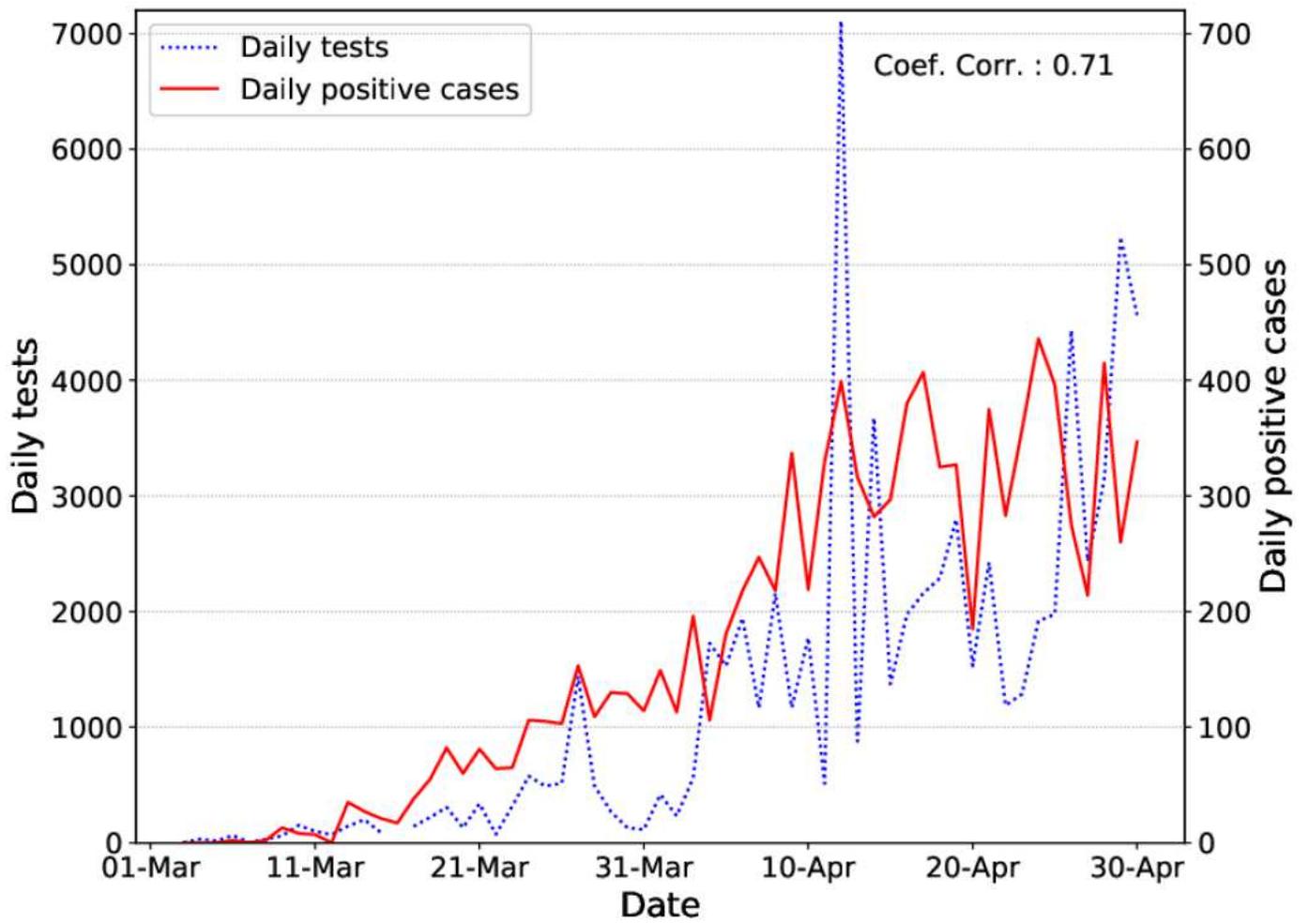


Figure 7

Time series of daily testing numbers taken by the government and daily new cases detected from the test.